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Land use Land Cover Dynamics and Fragmentation in Dimoria Block, Assam: A Geospatial Assessment

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ABSTRACT

Landscapes in urbanizing regions often undergo profound transformations that disrupt ecological balance and resource sustainability. This study examines the spatio-temporal dynamics of landuse and land cover in Dimoria Block, Assam, from 2010 to 2024, emphasizing the structural reorganization of the landscape through fragmentation analysis. Using geospatial techniques and quantitative landscape metrics, the research captures both the magnitude and spatial patterns of transformation. Findings reveal an accelerating shift from natural and agricultural surfaces toward urbanized land. Built-up areas significantly increased by 51.32 sq. km (11.48% relative increase), largely at the expense of agricultural land, which declined by 51.14 sq. km (-11.44%). Light vegetation and waterbodies also contracted (6.85 sq. km and 4.33 sq. km loss, respectively), while bare soil increased by 12.52 sq. km. Dense vegetation showed only a slight decrease of 1.52 sq. km. Fragmentation metrics indicate significant landscape reorganization. Built-up areas became more fragmented, with edge density (ED) increasing from 54.08 m/ha to 94.98 m/ha. Agricultural lands experienced decline in patch density (PD) and mean patch size (MPS). At the landscape level, the Contagion Index (CONTAG) decreased from 32.90% to 29.82%, indicating reduced clustering. Shannon's Diversity Index (SHDI) rose from 1.58 to 1.65, and Shannon's Evenness Index (SHEI) increased from 0.88 to 0.92, collectively showing heightened landscape heterogeneity and a more fragmented distribution of LULC types. These structural changes pose risks to biodiversity, hydrological stability, and local livelihoods, highlighting the ecological costs of unplanned land conversion. The study underscores the need for targeted landuse policies that integrate urban planning with conservation and agricultural preservation for sustainable land management in peri-urban environments.

Keywords: *LULC, Fragmentation, FRAGSTATS, GIS, Dimoria*

Introduction

Land, an essential natural resource, is the basis of the terrestrial ecosystem and human subsistence. Land cover refers to the physical characteristics of the earth's surface, including waterbodies, vegetation, and artificial objects; whereas landuse explains how human beings utilize the for various activities such as agriculture, urbanization, and conservation (A *et al.*, 2021). This intricate relationship between human and the Earth's surface has an influence in determining landscape changes and affecting ecological processes at local, regional, and global levels (Patra and Gavsker, 2021). According to (Lacher *et al.*, 2023), landuse land cover change (LULCC) is influenced by geography, economy, environment, and values of the local communities. This suggest that LULC pattern of a region is a result of socio-economic and natural parameters existing there and their exploitation by humans over the time and space (Agarwal *et al.,* 2019).

With the advancement of human societies, the effects on the land cover have become stronger, which also leads to evident changes in natural landscapes in wider areas (Schultz *et al*., 2017). LULC systems are extremely interconnected (Theobald, 2014) and evidently, the past 60 years have seen a 32 percent change in landuse as reported by (Zhao *et al*., 2025). This brisk pace at which LULC is changing because of the population rise, economic growth, and technological improvements, poses both threats and opportunities towards sustainable management of resources (Kamaraj and Rangarajan, 2022).

LULCC often lead to landscape fragmentation, where large, continuous habitats are broken into smaller, isolated patches, disrupting ecological connectivity and reducing habitat quality (Mulatu *et al.,* 2024). It is a situation when geographically an area of land is separated into parcels or patches, usually due to human activities. Fragmentation can change the abundance and density of patches, their size and shape, and enhance edge effects which can adversely affect ecosystem services, biodiversity, and the resilience of the natural system (Gómez-Fernández *et al.,* 2024; Mulatu *et al*., 2024). It also threatens local livelihoods and sustainable land management, especially in regions with rapid urbanization or post-conflict resettlement (Zheng *et al*., 2023). The spatial impacts of fragmentation are often most severe near urban centers and in areas of intensive land use change (Mulatu *et al*., 2024). Urban spaces in India have especially seen a notable growth at the cost of green and blue spaces in major cities like Darbhanga and in the east and the south of the country (Rath *et al*., 2022; Pal *et al*., 2024; Shahfahad *et al*., 2024). Additionally, research works conducted globally agree that agriculture and built-up areas have increased at the cost of forests, shrublands, and wetlands to create more fragmented and less connected landscapes (Castillo *et al*., 2022; Zheng *et al.,* 2023; Mulatu *et al*., 2024).

In the era of geospatial advancements, landscape metrics, remote sensing (RS), and geographic information systems (GIS) are becoming important tools to measure, analyze, and forecast LULCC patterns (Sharma *et al*., 2016; Talukdar *et al.,* 2021). Landscape metrics are quantitative measures used to describe the structure and composition of landscapes (Talukdar *et al*., 2021). These metrics are widely used to evaluate the performance of land change simulation models, track spatio-temporal dynamics and assess fragmentation or aggregation over time (Diksha *et al*., 2024). For example, the size of patches, patch density and largest patch index metric can indicate trends in habitat loss, urban sprawl, or agricultural encroachment, whereas edge density and contagion index are used to evaluate landscape connections and habitats isolation (Diksha *et al*., 2024). In general, these metrics offer a robust framework for quantifying and understanding complex LULC dynamics, providing effective policy and land management interventions (Diksha *et al*., 2024; Mulatu *et al*., 2024). Additionally, integration of RS and GIS enables accurate LULC classification with accuracies often exceeds 85% (Pham *et al.,* 2024; Zafar *et al*., 2024). Machine learning algorithms such as Support Vector Machine (SVM), Random Forest (RF) or hybrid models like CA-Markov enhance the precision of LULC mapping and future prediction (Pham *et al.,* 2024; Zafar *et al*., 2024). These integrated approaches have revealed rapid urban expansion, decline in agricultural land, and increased landscape fragmentation in diverse regions, with significant implications for ecosystem services, water quality, and sustainable land management (Diksha *et al.,* 2024; Hossain *et al.,* 2024). Studies using geospatial techniques have documented widespread conversion of forests and wetlands into agricultural and built-up areas, leading to a decline in natural habitats and increased fragmentation in regions like Madhya Pradesh, Manipur, Assam, and West Bengal (Singh *et al.,* 2018; Gabril *et al*., 2019; Devi and Shimrah, 2021; Pal *et al.,* 2024; Saha *et al*., 2024). A study by (Debnath *et al*., 2022) using geospatial techniques asserted that between 1973-2021, the Brahmaputra valley experienced a loss of 19.5 percent and 47.1 percent of vegetation and water bodies respectively. Contrastingly, built-up areas expanded at an unprecedented rate of nearly 385 percent. This trajectory is likely to continue the trend posing a threat to ecological balance and resource sustainability unless addressed. Likewise, urban expansion and agricultural intensification in Cachar and Nalbari districts of Assam using geospatial tools led to decreased vegetation and water bodies, increased built-up area and escalating land surface temperature giving rise to urban heat island effect and environmental stress (Ashwini and Sil, 2022;

Das *et al*., 2025). This synergy of RS, GIS and landscape metrics can therefore constitute a powerful tool in tracking, explaining and addressing changes in LULC, to aid in policy and planning choices (Zhao *et al*., 2024).

However, a critical research gap exists in the present area of interest despite the existence of LULC studies. For instance, a study by Kalita and Sharma (2015) in Dimoria Block revealed a significant decline in green cover from 1999 to 2013, with about an 11% reduction. Anthropogenic factors such as rapid urbanization, agricultural expansion, and insufficient enforcement of forest protection laws were identified as the primary causes. It has resulted in more non-forest land and greater fragmentation of forests, including areas outside reserved forests. Similarly, Deka (2020) conducted a study on the wetlands of Dimoria and revealed a rise in threats including encroachment, waste dumping, over-exploitation of its resources, and infrastructure development resulting in significant degradation and fragmentation of the landscape. While these studies have offered important insights into the region's LULC changes, they tend to focus on general trends and lack detailed spatio-temporal analysis of landscape structure and composition. Most notably, little has been done to quantify the extent and pattern of fragmentation, which is essential for understanding the ecological implications of LULCC. In addition, prior studies have focused on traditional classification methods, lacking the spatial metrics that reflect the complexity of land transformation processes.

The present study attempts to fill these knowledge gaps by conducting a comparative assessment of LULC dynamics over a 14-year time-frame, using a robust classification framework. It provides a comprehensive perspective on landscape transformation by integrating RS, GIS, and landscape metrics. Additionally, the study also examines the overall spatial configuration and heterogeneity of the landscape. These findings will eventually serve as an input to local management plans, ecological planning, and evidence-based policymaking in the face of ongoing environmental threat.

Materials and Methods

Study Area

The Dimoria CD Block is situated between 26°0′0″N to 26°10′14″N latitudes and 91°45′ 5″ E to 92°5′0″ E longitudes, respectively (Fig. 1). It is in the south-eastern part of Kamrup (Metropolitan) district of Assam. Bordered by Meghalaya to the south, Morigaon district to the northeast, and Guwahati city to the west, it covers an area of 447.07 square kilometers. It comprises 12 gaon panchayats, 144

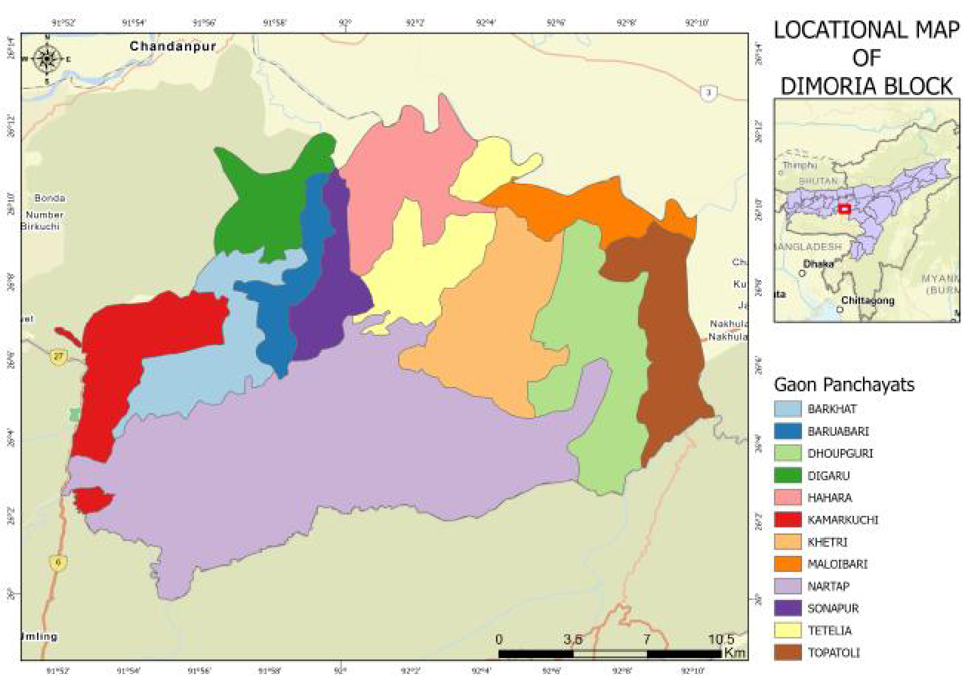

Fig.1. Location map of the study area

villages and a total population of 137,839 people (Directorate of Census Operations, Assam, 2011). The Brahmaputra River flows to the north of the block. Topographically, Dimoria exhibits a varied landscape of hills, plains, and isolated hillocks, representing an extension of the dissected Meghalaya plateau. Elevations range from 45 to 550 meters above mean sea level, with the northern part characterized by alluvial plains and the southern part by hilly terrain. Lateritic soil is prevalent in the region. Climate is subtropical monsoon, with an average annual rainfall of 1500 mm. Forests are classified as semi-evergreen to mixed deciduous, with patches of subtropical broad-leafed forests. The area is rich in timber resources, including Sal, Gomari, Nahar, Poma, and Simalu. Land use is predominantly shifting cultivation practiced by tribal communities, alongside settled agriculture.

Database Preparation

The methodological flowchart of the present study has been outlined in Fig. 2. Landsat 5 Thematic Mapper (TM) and Landsat 9 OLI/TIRS imageries at a resolution of 30 m were obtained from USGS Earth Explorer (https://earthexplorer.usgs.gov/) for the year 2010 and 2024 respectively (Table 1). The imageries were obtained for the same month to ensure temporal consistency, reduce seasonal variation which can contribute to a reliable change detection analysis. The advantage of using these imageries is

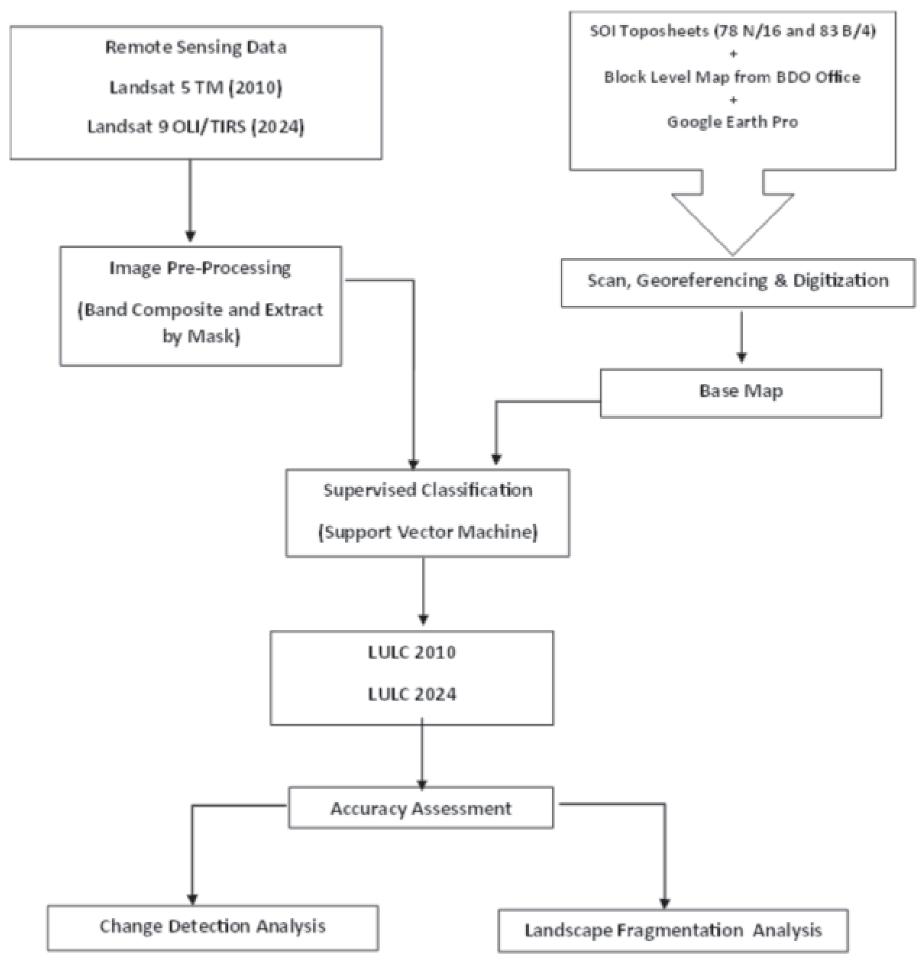

Fig. 2. Methodological flowchart of the present study

Table 1. Data Sources

Satellite-Sensor	Total Bands	Bands used for analysis	Path/Row	Acquisition Date
Landsat 5 TM	7	1,2,3,4,5,7	136/042	25/12/2010
Landsat 9 OLI/TIRS	11	2,3,4,5,6,7	136/042	23/12/2024

that they are Level-1 Collection 2 products of Landsat mission, which are already corrected for geometric distortions and radiometric calibration (https://www.usgs.gov/landsat-missions/). This pre-processing significantly reduces the data preparation workload and allows direct use for analysis. The imageries were loaded, stacked, and masked using the administrative layer of the study area in ArcGIS 10.3 platform.

Image Classification

Image classification refers to grouping image pixels into classes to create a thematic representation of distinct LULC classes (Maulik and Chakraborty, 2017). Among the several classification techniques, the supervised classification is considered to produce excellent results especially for large areas (Gislason *et al*., 2006; Ma *et al*., 2017; Kafy *et al*., 2021). A supervised, non-parametric learning method called the support vector machine (SVM) was used in the present study. It is widely used in LULC classification due to its ability to handle high-dimensional data and deliver robust results, even with limited training samples (Chowdhury, 2023). It is an effective classifier because it uses the optimal boundary (hyperplane) between different land cover classes in satellite imagery, making it robust when dealing with complex or heterogenous conditions (Halder *et al*., 2022). Studies have shown that SVM tends to perform better than standard classifiers such as Maximum Likelihood (Martins *et al*., 2016; Chatziantoniou *et al.*, 2017; Dapke, 2024). Although Random Forest and Artificial Neural Networks are slightly more accurate than SVM on some occasions, the latter is still a trusted, at least computationally inexpensive, when parameterized correctly and training data is scarce (Aryal *et al*., 2023; Chowdhury, 2023). Its versatility in the choice of kernel and capability to generalize well make SVM a popular choice in LULCC studies (Halder *et al*., 2022; Dapke, 2024). Six distinct classes were identified from both the imageries: light vegetation, waterbodies, built-up areas, agriculture, bare soil, and dense vegetation (Table 2). We collected 50 training samples (polygons) per class based on visual image interpretation and spectral characteristics of the features, ensuring a balanced class distribution throughout. The classification has been performed using ArcGIS Pro 2.8.

Post Classification

Accuracy assessment is an essential process for ensuring reliable mapping, typically using metrics such as user's accuracy (UA), producer's accuracy (PA), overall accuracy (OA) and kappa coefficient (Chowdhury, 2023). To examine the accuracy of a classified image, it is necessary to have both an interpreted map and a reference map or reference points (Kalita *et al.*, 2024). The reference or ground truth points were collected integrating field-based GPS locations and Google Earth Pro imageries for both the years. A total 200 accuracy points were used to generate the error or confusion matrix. The generated error matrix gives a multivariate agreement measure across the matrix's rows and columns, commonly known as Kappa coefficient (Sajan *et al*., 2022; Kalita *et al*., 2024). Its value ranges from -1 (complete disagreement) to 1 (perfect agreement), with 0 indicating agreement equivalent to chance (McHugh, 2012). It is calculated by (Cohen, 1960):

$$K_{hat} = (Observed - Expected)/(1 - Expected) \quad (1)$$

Table 2. Description of LULC Classes

LULC Classes	Description
Light Vegetation	Areas with sparse or short vegetation such as grasslands, shrubs, or degraded forests, typically with lower canopy cover and NDVI values less than dense vegetation.
Waterbodies	Natural or artificial surfaces covered by water year-round, including rivers, lakes, ponds, and reservoirs, easily identified by their unique spectral reflectance.
Built-up areas	Regions dominated by human-made structures such as buildings, roads, and other infrastructure, often associated with urban or peri-urban environments.
Agriculture	Land actively used for crop cultivation or managed pasture, including both irrigated and rainfed fields, often showing seasonal changes in vegetation cover.
Bare Soil	Exposed soil surfaces with little or no vegetation, such as fallow fields, construction sites, or eroded lands, typically with high reflectance in visible and infrared bands.
Dense Vegetation	Areas with high, continuous canopy cover such as forests, characterized by high NDVI values and low soil or built-up exposure.

Change Detection

Change detection analysis is a step to understand the transitisons over a specific time period from one certain kind of LULC class to another (Borah *et al.*, 2024). The analysis for the years 2010 and 2024 along with the generation of the change map was performed in QGIS 3.40.5 platform.

Landscape Fragmentation Analysis

Landscape fragmentation is assessed using a wide-range of measures known as landscape metrics (Sobhani *et al.*, 2021). These metrics can be easily evaluated using FRAGSTATS 4.2.681 software. It manages LULC patterns by investigating land diversity, classification of a landscape mosaic and the exploration of a landscape gradient. The software computes these metrics at three levels- patch-level, class-level, and landscape-level (McGarigal and Marks, 1995). However, in our study we have considered only class-level and landscape-level metrics to capture broader spatial and fragmentation patterns among LULC categories. Among the class-level metrics, percentage of landscape (PLAND), number of patches (NP), patch density (PD), mean patch size (MPS) and edge density (ED) were considered because they together help quantify and monitor changes in landscape structure caused by anthropogenic or natural factors (Liu and Weng, 2013; Sertel *et al.*, 2018; Masoudi *et al.*, 2024). PLAND shows how much area each land cover type occupies, NP and PD indicate how fragmented or numerous the patches are, MPS reflects the average size of these patches, and ED measures the complexity of boundaries between land cover types (Masoudi *et al.*, 2024). For the landscape-level metrics, the Contagion Index (CONTAG), Shannon's Diversity Index (SHDI) and Shannon's Evenness Index (SHEI) were used. These indices together give an idea of how LULC changes affect landscape structure, diversity, and ecological stability, aiding better land management and conservation decisions (Das and Sarkar, 2023; Dai *et al.*, 2024; Wang *et al.*, 2024). CONTAG shows how clustered land cover types are, SHDI measures the variety of land cover types, and SHEI shows how evenly they are distributed (Das and Sarkar, 2023; Han *et al.*, 2023).

Results

The present section is divided into two sub-sections: first, LULC changes and accuracy assessment have been analyzed. Second, analysis of landscape fragmentation statistics.

LULC Change Analysis and Accuracy Assessment

Accurate LULC assessment is crucial to understand environmental changes, resource management, and sustainable development (Nedd *et al.*, 2021; Wang *et al.*, 2023). LULC maps for the years 2010 (Fig. 3) and 2024 (Fig. 4) show the spatial extent and distribution of LULC changes in Dimoria. The region being categorized into six distinct classes: Light Vegetation, Waterbodies, Built-up areas, Agriculture, Bare Soil, and Dense Vegetation, shows significant transitions

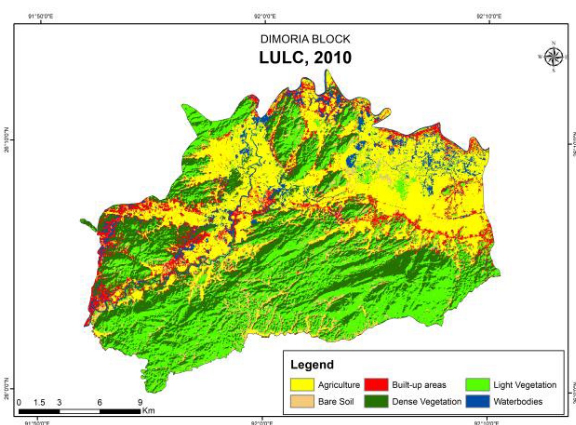

Fig. 3. LULC Map, 2010

Table 3. Change Detection Matrix (2010-2024)

LULC Classes	Area in sq. km (2010)	Area in sq. km (2024)	Net Change (in sq. km)	Net Change (%)
Light Vegetation	129.33	122.49	-6.85	-1.53
Waterbodies	23.16	18.83	-4.33	-0.97
Built-up areas	39.08	90.41	51.32	11.48
Agriculture	121.34	70.19	-51.14	-11.44
Bare Soil	22.52	35.04	12.52	2.80
Dense Vegetation	111.65	110.13	-1.52	-0.34

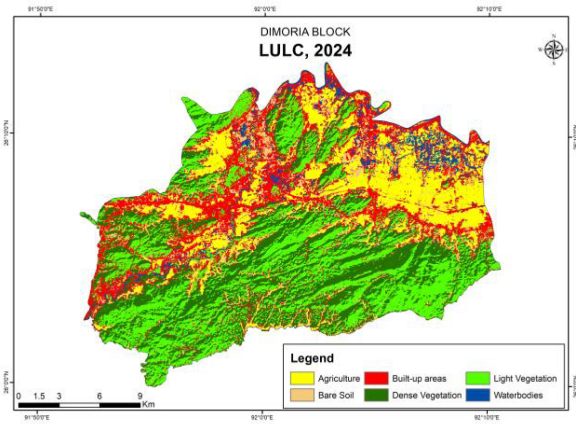

Fig. 4. LULC Map, 2024

in the past 14 years (Table 3).

Light Vegetation: Light vegetation declined from 129.33 sq. km to 122.49 sq. km with a net loss of 6.85 sq. km (–1.53%). This moderate loss is usually attributed to the pronounced effects of urbanization and land clearing. Studies show that encroachment, land clearing, and concrete growth are key drivers of moderate vegetation loss (Tang *et al.*, 2018; Wieczorkowski and Lehmann, 2022; Ding *et al.*, 2024).

Waterbodies: Waterbodies reduced from 23.16 sq. km to 18.83 sq. km in the past 14 years, with a net loss of 4.33 sq. km. The key drivers include land reclamation, waste dumping, seasonal shrinkage or water diversion activities. These factors have also been acknowledged as root causes of waterbody decline in studies by (Talukdar and Pal, 2017; Shah *et al.*, 2020; Xiao *et al.*, 2022).

Built-up areas: Built-up areas demonstrated the most prominent change, increasing from 39.08 sq. km in 2010 to 90.41 sq. km in 2024, resulting in a net gain of 51.32 sq. km (an increase of 11.48% in relative area share). The result is consistent with global and regional studies showing rapid urban expansion driven by urbanization, population growth, and infrastructure development (Fenta *et al.*, 2017; Naikoo *et al.*, 2024).

Agriculture: Conversely, agricultural land declined surprisingly by 51.14 sq. km, representing an 11.44% decrease in proportional coverage. This reduction suggests a large-scale conversion of agricultural land into urban and non-agricultural uses. Similar decline in agricultural land is well-documented in studies by (Rondhi *et al.*, 2018; Tufa and Megento, 2022; Saqib *et al.*, 2024), where rapid urban expansion and conversion to non-agricultural uses have been acknowledged.

Bare Soil: Bare soil increased from 22.52 sq. km to 35.04 sq. km, with a net gain of 12.52 sq. km (2.80%). This increase in bare soil area is primarily attributed to landuse changes, overgrazing, and vegetation loss, which is also validated in studies by (Demattê *et al.*, 2020; Hill and Guerschman, 2022).

Dense Vegetation: Dense vegetation which includes mainly the protected areas remained relatively stable, showing only a slight decrease of 1.52 sq. km (–0.34%). Studies indicate high dense and diverse vegetation forms a good line of defense against degradation, with minimal recorded losses (Bordoloi and Ng, 2020; Ohler *et al.*, 2023; Lann *et al.*, 2024).

Fig. 5-7 clearly illustrate the significant urban expansion and land transformation during the study period, showing a marked increase in built-up and barren surfaces at the expense of agricultural and vegetative land covers.

Accuracy assessment statistics revealed Kappa Coefficient is 0.86 for 2010 and 0.88 for 2024, suggesting a high level of agreement between the classified maps and the reference data. The overall accuracy improved from 88.50% in 2010 to 91.05% in

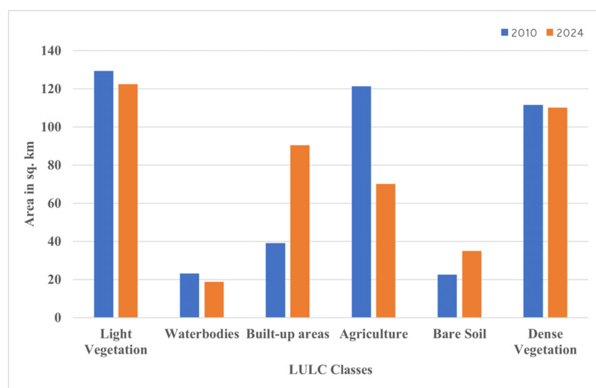

Fig. 5. LULC Change in Dimoria (2010-2024)

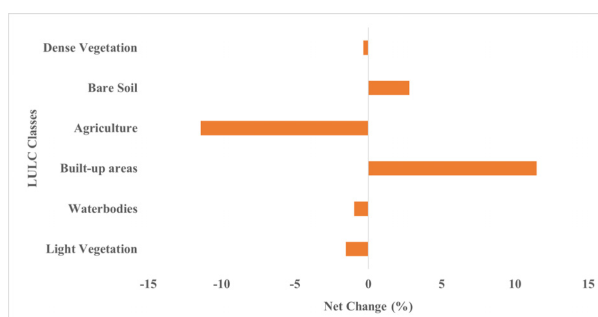

Fig. 6. Gains and Losses for different LULC classes

2024, respectively. User's and producer's accuracies also remained significantly higher (>=85%), supporting the robustness of our classification (Table 4). In LULC studies, Kappa value above 0.8 is considered almost perfect (Landis and Koch, 1977; Rwanga and Ndambuki, 2017). Hence, our classification is consistent with the real-world context.

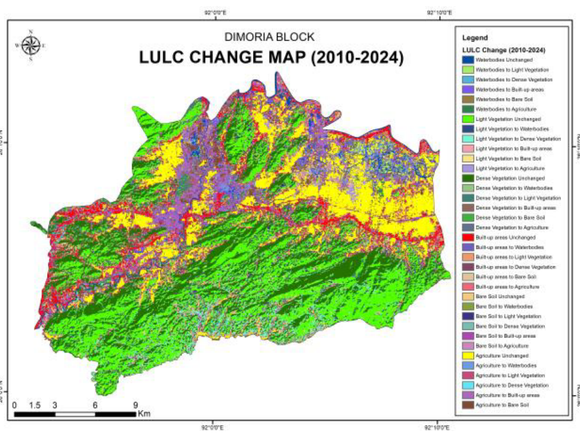

Fig. 7. LULC Change Map, 2010-2024

Landscape Fragmentation Analysis

Landscape fragmentation analysis revealed a significant anthropogenic impact on the LULC pattern of the study area. Table 5 and 6 shows the class-level metrics while Table 7 shows the landscape-level metrics for both the years.

Light Vegetation: Light vegetation experienced a moderate reduction in area, with PLAND decreasing from 28.93% in 2010 to 27.40% in 2024. This reduction is accompanied by a combined decrease in NP, PD, ED, and MPS. It shows that light vegetation patches have become fewer, slightly smaller, and less fragmented, suggesting land conversion (Taiwo *et al*., 2023; Wang and Afla, 2024).

Waterbodies: The area occupied by waterbodies saw a slight decline, with PLAND falling from 5.18% to 4.21%. The decline in NP, PD, ED, and NPS suggest a contraction in water body coverage, with fewer and more isolated water patches across the landscape. This could be a sign of drying out of smaller ponds, infilling or direct conversion. This also aligns with concerns about wetland degradation in urbanizing areas of Assam (Bhuyan and Deka, 2024; Saha *et al*., 2024).

Built-up areas: Built-up areas experienced the most dramatic transformation, with PLAND increasing from 8.74% in 2010 to 20.22% in 2024, indicating substantial urban expansion. NP and PD also increased but ED increased notably. The massive increase in ED from 54.08 m/ha to 94.98 m/ha indicates irregular, sprawling development creating extensive interfaces with other land uses and increasing edge effects. MPS grew from 0.78 ha to 1.28 ha, indicating not only the emergence of new urban patches but also the merging of smaller urban clusters into larger, more consolidated settlements. This twin tendency towards greater fragmentation and aggregation is typical of urban sprawl. The fragmentation measures provide graphic demonstration of the morphology of this sprawling which is an important finding, identifying the direct human influence (Irwin and Bockstael, 2007; Das and Angadi, 2020; Rath *et al*., 2022).

Agriculture: Agriculture has experienced a massive loss in overall area. It shows a significant decline, with PLAND dropping from 27.14% to 15.70%. The decline in NP, PD, ED, and MPS together suggests that agricultural lands are being lost, broken up, or converted, likely into built-up or bare soil. This demonstrates landuse change as well as a decline in strength of the structural integrity of the agricultural

Table 4. Accuracy Assessment of LULC for 2010 and 2024

LULC Classes	2010		2024	
	User's Accuracy (%)	Producer's Accuracy(%)	User's Accuracy (%)	Producer's Accuracy (%)
Light Vegetation	90.63	87.88	91.50	89.60
Waterbodies	85.00	94.00	88.00	94.50
Built-up areas	93.94	100.00	96.00	97.00
Agriculture	93.94	83.00	90.50	91.00
Bare Soil	85.00	85.71	87.50	89.00
Dense Vegetation	87.50	85.00	92.00	90.00
Overall accuracy (%)	88.50	91.05		
Kappa coefficient	0.86	0.88		

landscape that can have ramifications on food security and rural livelihoods (Molotoks *et al*., 2020; Parven *et al*., 2022; Zhang *et al*., 2024). Fragmentation metrics capture the direct consequence of urban expansion onto agricultural land, a common phenomenon in peri-urban regions (Tu *et al*., 2023).

Bare Soil: Bare soil expanded significantly in area and became massively fragmented. It saw an increase in area, with PLAND rising from 5.04% to 7.84%. The huge increase in NP and PD suggests that new areas are being cleared (for construction or other disturbances) and existing bare areas are being broken up into numerous small, scattered patches. The ED increase confirms this irregular and highly dispersed pattern. This is a common indicator of active construction and land disturbance associated with urbanization and suggest unsustainable nature of land change (Dadashpoor *et al*., 2019; Bindajam *et al*., 2023).

Dense Vegetation: Dense vegetation maintained a relatively stable area (PLAND decreased slightly from 24.97% to 24.63%), but the spatial structure changed meaningfully. The significant decrease in NP and PD, slight drop in ED and a moderate increase in MPS, indicate many smaller, fragmented patches of dense vegetation have been lost or consolidated into larger ones. This could mean that smaller, separate dense vegetation areas are removed, while bigger connected areas stay or grow (e.g., in protected zones or bigger forests that resist fragmentation more effectively). It is a net loss of overall area, but the remaining areas are slightly larger on average, perhaps showing loss of peripheral small fragments (Ramalho *et al*., 2014; Liu *et al*., 2016).

Landscape structure changed from 2010 to 2024, is also evident in landscape metrics. The Contagion Index (CONTAG) dropped from 32.90% to 29.82%, indicating less clustering of land cover. This decrease implies the landscape is now more broken up and varied, with land patches more spread out and less clustered. Such a trend is commonly associated with increasing anthropogenic influence, particularly urban expansion and infrastructure development, which disrupt large, continuous land cover blocks. Conversely, both SHDI and SHEI increased, with SHDI from 1.58 to 1.65 and SHEI from 0.88 to 0.92 during the same period. A rise in SHDI indicates more land cover diversity, showing a wider range of LULC types. Meanwhile, a higher SHEI indicates a more balanced distribution among these classes, with no single land cover type dominating the landscape.

These changes signify a transition toward a more compositionally diverse and fragmented landscape. The metrics reveal the growing complexity of land cover patterns, likely driven by intensified landuse pressures. When interpreted alongside class-level

Table 5. Class-Level Metrics for 2010

LULC Classes	PLAND (%)	NP	PD (numbers/100 ha)	ED (m/ha)	MPS (ha)
Light Vegetation	28.93	3622.00	8.10	85.51	3.57
Waterbodies	5.18	3104.00	6.94	29.14	0.75
Built-up areas	8.74	5029.00	11.25	54.08	0.78
Agriculture	27.14	1956.00	4.38	55.12	6.20
Bare Soil	5.04	4341.00	9.71	35.50	0.52
Dense Vegetation	24.97	3313.00	7.41	72.00	3.37

Table 6. Class-Level Metrics for 2024

LULC Classes	PLAND (%)	NP	PD (numbers/100 ha)	ED (m/ha)	MPS (ha)
Light Vegetation	27.40	3538.00	7.91	75.69	3.46
Waterbodies	4.21	2892.00	6.47	24.38	0.65
Built-up areas	20.22	7043.00	15.75	94.98	1.28
Agriculture	15.70	1874.00	4.19	36.62	3.75
Bare Soil	7.84	6641.00	14.85	56.13	0.53
Dense Vegetation	24.63	2403.00	5.37	67.23	4.58

Abbreviations: PLAND (Percentage of Landscape), NP (Number of Patches), PD (Patch Density), ED (Edge Density), MPS (Mean Patch Size) fragmentation indicators, these landscape metrics offer a comprehensive understanding of how both the structure and composition of the landscape are evolving.

Table 7. Landscape-Level Metrics for 2010 and 2024

Years	CONTAG (%)	SHDI	SHEI
2010	32.90	1.58	0.88
2024	29.82	1.65	0.92

Abbreviations: CONTAG (Contagion Index), SHDI (Shannon's Diversity Index), SHEI (Shannon's Evenness Index)

Discussion

A significant LULCC and landscape fragmentation analysis of Dimoria during 2010 to 2024 aids in understanding the vast landscape transformation being observed.

Dimoria has undergone significant changes in LULC, with built-up areas almost doubling (an increase of 11.48%) because of swift urbanization. This is clear in the increased NP, PD, and ED values, which suggest irregular and scattered growth. This urban expansion has primarily come at the cost of agricultural land. The reduction in PLAND, NP, PD, ED, and MPS shows fragmentation and weakening agricultural landscapes. Such situations open the door to food insecurity affecting rural livelihoods (Saqib *et al*., 2024; Zhang *et al*., 2024). Losing farmland and vegetation is exacerbated by human activities such as encroachment, waste disposal, and the use of chemical fertilizers and pesticides in nearby croplands, which destabilize ecosystems. Overuse of water and biological resources, along with infrastructure projects like roads and railways, has increased landscape fragmentation and ecological stress in the study area. These changes align with the documented decline of wetlands in the area. Industrial waste, especially from the now-defunct Nagaon Paper Mill, has had a lasting impact on the water quality of the region. Consequently, several wetlands have been permanently converted to agriculture during dry seasons, leading to habitat loss and hydrological disruption (Deka, 2020). These pressures not only reduce water availability and quality but also heighten biodiversity risks (Agrawal *et al*., 2021; Moi and Teixeira-De-Mello, 2021). Vegetation cover has also seen substantial changes from 1999 to 2013 in the study area as revealed in the study by (Kalita and Sharma, 2015). The total green cover decreased by nearly 10% and settlement areas increased by about 11%. This reduction was particularly severe outside reserved forests. Although reserved forests are relatively resilient, they still experienced a notable 7.25% decline in green cover. This pattern as seen in their study underscores the broader trend of landscape degradation, where peripheral areas are more susceptible to clearance and conversion than core forest zones. Likewise, in our study, dense vegetation showed relative stability, with only a slight 0.34% decline, but fragmentation analysis revealed consolidation of larger patches and loss of smaller ones, highlighting the vulnerability of marginal forest areas. Evaluation of landscape-level metrics shows a decrease in CONTAG and an increase in SHDI and SHEI. This suggests an increase in fragmentation, reduced clustering and greater LULC diversity. It largely represents a patchwork of fragmented urban, agricultural, and disturbed lands rather than a naturally diverse ecosystem (Taiwo *et al*., 2023; Wang *et al*., 2023; Zheng *et al*., 2023; Romanillos *et al*., 2024).

Collectively, these transformations emphasize the accelerating pace of urbanization, agricultural decline, wetland degradation, and forest cover loss in Dimoria, underscoring the urgent need for integrated land-use planning, restoration, and targeted conservation strategies. The results underscore the need for sustainable land-use policies in Dimoria, with a focus on wetland protection, conservation of surrounding vegetation, and preservation of farmland from uncontrolled urban growth. Integrating ecological restoration with development planning will be critical to maintaining biodiversity, securing livelihoods, and ensuring long-term environmental sustainability in the region.

Conclusion

This extensive geospatial evaluation of LULC dynamics and fragmentation within Dimoria Block provides a detailed depiction of a landscape undergoing significant anthropogenic alterations. The results underscore a notable and rapid expansion of built-up areas at the cost of agricultural land, light vegetation, and waterbodies. A more thorough examination of fragmentation parameters has unveiled a notable structural transformation in dense vegetation, showing either the diminishment or aggregation of smaller, isolated fragments. Macroscopic indicators, such as a decrease in the Contagion Index alongside simultaneous increases in Shannon's Diversity and Evenness Indices, affirm a transition towards a fragmented, diverse, and increasingly human-altered setting. These documented alterations carry significant implications for local ecosystem services, biodiversity, and environmental adaptability, emphasizing the critical necessity for proactive spatial planning. It is imperative to recognize that the findings of this study are limited by the spatial resolution of the remote sensing data which may constrain identifying fine-scale alterations. Future investigations should encompass socio-economic determinants, leverage datasets of higher resolution, and use predictive modeling to predict forthcoming LULC scenarios. From a policy viewpoint, the results underscore the imperative nature of implementing land-use zoning to oversee urban expansion, preserving and rehabilitating waterbodies especially wetlands to uphold hydrological and ecological roles, and advocating for sustainable agricultural practices and agroforestry to safeguard arable land and rural livelihoods. Regular geospatial surveillance and evidence-grounded regional planning, accentuating compact urban expansion, conservation of sensitive regions, and establishing climate-resilient infrastructure, are indispensable for harmonizing developmental ambitions with the enduring ecological well-being in Dimoria Block.

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